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Forecasting Maritime and Financial Market Trends: Leveraging CNN-LSTM Models for Sustainable Shipping and China's Financial Market Integration

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Abstract: With the acceleration of economic globalization, China's financial market has emerged as a vital force in the global financial system. The Baltic Dry Index (BDI) and China Container Freight Index (CCFI) serve as key indicators of the shipping sector's health, reflecting their sensitivity to shifts in China's financial landscape. This study utilizes an innovative CNN-LSTM deep learning model to forecast the BDI and CCFI, using 25,974 daily data points from the Chinese financial market between 5 May 2015 and 30 November 2022. The model achieves high predictive accuracy across diverse samples, frequencies, and structural variations, with an R^2 of 97.2%, showcasing its robustness. Beyond its predictive strength, this research underscores the critical role of China's financial market in advancing sustainable practices within the global shipping industry. By merging advanced analytics with sustainable shipping strategies, the findings offer stakeholders valuable tools for optimizing operations and investments, reducing emissions, and promoting long-term environmental sustainability in both sectors. Additionally, this study enhances the resilience and stability of financial and shipping ecosystems, laying the groundwork for an eco-friendly, efficient, and sustainable global logistics network in the digital era.

Keywords: China's financial market; Baltic Dry Index (BDI); China Container Freight Index (CCFI); CNN-LSTM model; deep learning; sustainable shipping

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1. Introduction

The maritime industry is essential for the facilitation of global commerce and the substantial contribution to GDP growth in numerous countries [1]. It is the backbone of international trade. The maritime sector is inextricably linked with China's financial market, which is a critical component of the global financial system, thereby contributing to global economic prosperity. The BDI and the CCFI are critical barometers of market dynamics [2]. The Baltic Exchange's BDI serves as an indispensable benchmark for assessing freight pricing trends and assessing shipping expenses [3]. Conversely, the CCFI, which monitors container freight rates in China, is a critical indicator of financial and freight rate fluctuations within the nation, demonstrating their substantial impact on the global supply chain [4]. These indices are essential for understanding the substantial impact of international freight transport on a nation's GDP [5].

The integration of data from China's financial markets with the BDI and CCFI improves maritime trend forecasting in terms of sustainability. This integration allows stakeholders to implement strategies that optimize fuel consumption, reduce emissions, and foster long-term environmental sustainability in global trade [6]. It is imperative to accurately forecast the BDI and CCFI, as these indices are essential for strategic planning, risk mitigation, and market trend analysis [7]. In recent years, there has been a substantial increase in the volume of academic and industry research on these indices, which has consolidated their status as forward-thinking economic indicators. Incorporating data from China's financial markets into the forecasting of the BDI and CCFI is therefore essential, as investors, financial analysts, and shipping companies rely on these metrics to evaluate the health of China's financial markets and the global maritime shipping industry [8]. This integration is essential for the optimization of global supply chains, the development of sustainable maritime logistics and financial strategies, and the refinement of China's financial sector. Ultimately, this will enhance the efficiency and sustainability of international trade.

In spite of extensive research, there is a substantial lacuna in the literature regarding the utilization of Chinese financial market data to forecast the BDI and CCFI. The BDI and CCFI have been the subject of prior research that has predominantly focused on three critical research areas: their role as macroeconomic indicators [9,10], their quantitative relationships with commodity markets [11,12], and the methodological challenges associated with accurate forecasting [2,6]. The BDI and CCFI have been employed by academicians in the initial area to assess market expectations regarding the global economy and trade. These indices are frequently employed in academic research to predict a variety of economic indicators, such as energy consumption, demand for basic materials, agricultural transportation, inflation trends, and exchange rate fluctuations [9,10]. The second research area examines the quantitative relationships between the BDI, CCFI, and global commodity markets, examining the ways in which these indices influence the prices of commodities such as oil, metals, and agricultural products [11,12]. Lastly, the third area discusses the methodological challenges associated with forecasting the BDI and CCFI, which are a result of the nonlinearity, non-stationarity, and high sensitivity of these indices to a diverse range of external factors [2,6]. Traditional econometric forecasting models frequently depend on assumptions of causality and data regularity; however, the predictive reliability and accuracy of BDI and CCFI data are frequently compromised by their distinctive characteristics [13–16].

Empirical evidence has consistently shown that AI-based approaches outperform traditional models. As a result, AI methodologies, including support vector machines (SVMs), artificial neural networks (ANNs), and nonlinear regression, have increasingly been adopted for analyzing and predicting the BDI and CCFI [17,18]. However, individual AI prediction methods are prone to errors due to inherent limitations, such as overfitting or underfitting, leading researchers to approach single machine learning techniques with caution [12]. Despite the wealth of research on BDI and CCFI trends, reliable forecasting based on multivariate data remains a substantial challenge due to the complex nature of BDI and CCFI data. Recognizing this challenge, this paper poses two central research questions:

1. Which Chinese financial indicators are most predictive of the BDI and CCFI?
2. What forecasting models are most effective in enhancing the precision of BDI and CCFI forecasts?

To address these research questions and bridge the gap in BDI and CCFI forecasting research, this study utilizes an innovative integrated deep learning model. The model combines CNN and LSTM networks, trained on a comprehensive dataset of daily pricing data from 5 May 2015 to 30 November 2022, consisting of 25,974 observations. The results indicate that the CNN-LSTM model excels in identifying nonlinear features and capturing intricate volatility patterns. For predicting both the BDI and CCFI, the model achieves an impressive R^2 value of 97.2%, significantly outperforming standalone CNN and LSTM models. Furthermore, the model demonstrates remarkable adaptability to random sample selection, varying data frequencies, and structural changes within the sample population, effectively navigating the dynamic landscapes of financial and supply chain markets.

This paper makes several key contributions. First, it introduces the novel CNN-LSTM integrated model to the field of deep learning, specifically designed to leverage the extensive data available from China's financial market. By capturing the complex, nonlinear, and time-varying dynamics of the supply chain market, the model provides more accurate forecasts for the BDI and CCFI. Second, this study expands the application of machine learning techniques into finance and maritime management, offering a deeper understanding of the intricate relationships between China's financial market and the maritime industry. The findings highlight the significant potential of China's financial market in forecasting BDI and CCFI. Beyond forecasting, the model also serves as a valuable tool for monitoring shipping rate challenges, enabling stakeholders to adjust portfolios and strategies, fostering sustainable trade growth, ensuring financial market stability, and supporting resilient supply chain transformation. Additionally, by offering insights that can optimize operational efficiency and reduce fuel consumption, the model contributes to lowering the carbon footprint of maritime logistics, aiding the shift toward more environmentally sustainable shipping practices.

The structure of this study is as follows: Section 2 outlines the methodology for forecasting the BDI and CCFI and provides a thorough review of the existing literature in the Chinese financial context. Section 3 details the data sources and integration techniques. Section 4 presents a comparative analysis of the empirical results for the BDI and CCFI, contrasting them with other competing models. Finally, Section 5 synthesizes the study's conclusions, addresses its limitations, and suggests directions for future research.

2. Literature Review

2.1. BDI Forecasting Study

In the fields of shipping economics and finance, the BDI has attracted substantial scholarly attention as a critical indicator of the health and performance of the international shipping industry. The transportation sector's inherent volatility and complexity present significant obstacles to the accurate prediction of BDI. BDI forecasting has long been conducted using conventional statistical methods, including regression models, time series analysis, and artificial neural networks (ANNs). For example, ref. [19] developed the V-AAR model, which utilizes unit root and cointegration techniques in time series analysis to capture the cyclical dynamics of the BDI. Using the Zhao–Atlas–Marks bi-linear time–frequency representation, ref. [20] conducted a time–frequency analysis of the periodic properties of the BDI, building upon this foundation. A mainstay in time series analysis, ARIMA models are widely used to identify temporal dependencies and trends within BDI data. However, ref. [21] demonstrated that vector autoregressive (VARX) models with exogenous variables can outperform ARIMA models in BDI forecasting accuracy.

The limitations of conventional methods in modeling the BDI's unpredictable, nonlinear behavior have been illustrated by recent developments in machine learning techniques. Traditional time series models are unable to accurately represent the intricate dynamics of the BDI, as indicated by empirical evidence [22,23]. Furthermore, conventional econometric models are unable to fully reveal the dry bulk freight index's nonlinear characteristics [15]. ANNs, which are renowned for their capacity to learn from intricate, nonlinear data patterns, have demonstrated promising results as alternatives. They have been effectively implemented on BDI time series data, thereby revealing latent patterns and producing more precise forecasts [9]. For instance, ref. [15] contributed to the field by introducing dynamic factor networks (DFNs) for BDI forecasting, thereby illustrating that ANN-based predictions can surpass conventional econometric models. Ref. [24] improved BDI forecasting by incorporating wavelet transform denoising into a support vector machine (SVM) combinatorial model. Ref. [25] verified the efficacy of ANNs, demonstrating that they outperform conventional methods such as the Box–Jenkins approach, analysis of variance (ANOVA), and vector autoregression (VAR). Neural network-based models have consistently exhibited their capacity to generate precise forecasts and manage intricate, nonlinear relationships.

Hybrid approaches that integrate a variety of forecasting techniques have gained popularity in order to harness the strengths of diverse models. These approaches capitalize on the unique advantages of each model to enhance predictive accuracy [11]. For instance, ref. [14] demonstrated the effectiveness of this method by incorporating multiple discrete models into a composite structure, thereby substantially improving the accuracy of BDI forecasting. The Deep Integrated Recurrent Network (DIRN) model was introduced in [26]. This model integrates elements from recurrent neural networks (RNNs), LSTM networks, and gated recurrent units (GRUs) to optimize predictive performance. The DIRN model consistently outperformed traditional methods such as ARIMA and Multi-Layer Perceptron (MLP), as well as standalone RNN, LSTM, and GRU models, in both short- and long-term forecasting horizons. This underscores the efficacy of hybrid models that capitalize on the complementary strengths of various architectures. Nevertheless, neural networks are adept at feature extraction; however, they face difficulties in hyperparameter optimization and training efficiency, resulting in a significant gap in BDI prediction research for integrated frameworks. The present study employs an innovative deep learning model that combines LSTM and CNN architectures to address this gap, with the objective of significantly enhancing the accuracy of BDI prediction.

2.2. CCFI Forecasting Study

In 1998, the Shanghai Stock Exchange [27] established CCFI as a pioneering initiative to keep pace with the rapid expansion of China's container transportation sector. The purpose of this initiative was to provide the industry with a standardized metric for predicting and evaluating fluctuations in freight rates [28]. The CCFI is a comprehensive resource that collects data from the services of 22 prominent companies, collectively controlling a substantial portion of the market [29]. It includes both spot and contract freight rates. The global containerized trade landscape is populated by a variety of companies, ranging from smaller enterprises to major players. The CCFI provides a thorough evaluation of the dynamics of freight rates in China's export container sector, which encompasses both spot and forward rates at ten critical Chinese ports: Dalian, Tianjin, Qingdao, Shanghai, Nanjing, Ningbo, Xiamen, Fuzhou, Shenzhen, and Guangzhou. These ports not only are among the largest in the world in terms of container handling volumes but also serve as critical nodes for outbound container services from the Far East, establishing the CCFI as a dependable regional metric. The index is additionally fortified by data contributions from 22 prominent international liner companies, including CMA-CGM, Hamburg Line, COSCO, Maersk, and Hapag-Lloyd [30].

In the container shipping industry, the CCFI is frequently used as a benchmark in forward rate agreements or as a floating component in index-linked container contracts, and it holds considerable significance [31]. The CCFI is widely recognized as the second most influential freight rate index globally, second only to the BDI, and is regarded as a critical freight indicator for the global container trade [27,32]. It is also regarded as a vital indicator of the health of China's shipping industry. Despite the emergence of alternative container freight indices, including the Global Container Index (WCI) by Drewry; the Ningbo Container Freight Index (NCFI) from the Ningbo Shipping Exchange (NSX); the Baltic Global Container Freight Index (FBX); and the Xeneta Shipping Index, which was launched by freight rate benchmarking organizations in 2021, the CCFI continues to garner significant scholarly attention.

Ref. [33] proposed a forecasting model that utilizes the CCFI as its foundation and integrates empirical mode decomposition with gray-wave forecasting methods. Their model applies a generalized gray model (GM) for trend forecasting and a gray-wave model for cycle forecasting, decomposing time series data into long-term trends and short-term cycles.. This hybrid approach significantly enhances the accuracy of forecasting, offering valuable decision support to practitioners who are involved in risk hedging through forward rate agreements. Ref. [28] also investigated the application of the ARIMA multivariate modeling framework to predict CCFI performance by incorporating soft survey sentiment and confidence information as variables. In comparison to a basic ARIMA model, the ARIMAX model demonstrated superior forecasting accuracy when supplemented with this additional soft information, according to their research. Nevertheless, there is a substantial gap in the research that directly connects the CCFI with the Chinese futures market, despite these advancements.

2.3. Financial Market Research

Financial markets play a pivotal role in the global economy, providing essential functions such as price discovery, risk management, and opportunities for investment speculation. Their impact is significant, contributing to economic stability, fostering financial innovation, and enhancing market efficiency [34]. A central theme in financial market research is price volatility analysis, as volatility greatly influences trading decisions and risk management strategies. Extensive research has explored the drivers of price volatility across diverse sectors, employing various statistical and econometric models [35]. These analyses cover a range of markets, including freight transport [36], stock markets [37–40], energy markets [41,42], agricultural commodities [43], and metals [44].

With growing academic interest in commodity financial markets, the interaction between financial markets and these sectors has emerged as a valuable research focus [45]. Ref. [46] contributes to this field with the development of RHINE, a nonlinear regime-switching model that captures the dynamic behaviors and interdependencies within financial ecosystems composed of multiple time series, demonstrating improved predictive performance over traditional methods. Similarly, ref. [39] introduces SMP-DL, a system for stock market prediction leveraging LSTM and BIGRU models, which has shown enhanced forecasting accuracy. In another study, ref. [40] explores various deep learning approaches, including MLP, RNN, LSTM, and CNN, for stock price prediction. Their findings indicate that CNN is the best performer, even in scenarios where it is trained on one stock exchange and tested on another, outperforming the traditional ARIMA model in forecasting trends.

Research on the operational efficiency of financial markets has also highlighted key factors such as regulatory reforms, speculative activities, and information efficiency [47,48]. For instance, ref. [12] investigates the relationship between the BDI and commodity prices, revealing an asymmetric connection that offers valuable insights into the informational content of financial prices and the opportunities they present. Additionally, research has examined the impact of external factors, such as macroeconomic indicators, policy shifts, and technological advancements, on financial market dynamics. These studies have focused on how such factors affect market volatility, price discovery processes, and liquidity [45].

In recent years, the application of machine learning algorithms to financial market research has surged. Neural networks and ensemble methods are now central tools in developing automated trading strategies, forecasting financial prices, and recognizing complex patterns [12]. These algorithms offer strong potential for both accuracy and robustness in predictions. For instance, ref. [49] conducted a comparative study on stock index forecasting across six different markets, evaluating ARIMA, LSTM, and BILSTM models, and demonstrated that the BILSTM model significantly improved forecasting accuracy. Meanwhile, ref. [50] employed a BILSTM-Attention-CNN framework for crude oil price forecasting, effectively leveraging advanced deep learning denoising techniques.

However, despite these advancements, there remains a notable research gap concerning the relationship between the BDI, CCFI, and financial markets, particularly within the context of the Chinese financial market. To address this gap, we propose a novel hybrid deep learning architecture that combines CNN and LSTM components. This model is designed to forecast both the BDI and CCFI using comprehensive daily data from the Chinese financial market, not only enhancing prediction accuracy but also supporting sustainable development. By enabling stakeholders to make more informed decisions, this approach helps optimize fuel consumption, reduce emissions, and promote environmental sustainability in global trade.

3. Research Methodology

3.1. Data Description

This paper presents the development of a model that leverages three distinct datasets to explore the relationship between financial markets and supply chains. The CNN-LSTM model is employed due to its unique ability to handle both spatial and temporal dependencies, making it ideal for forecasting complex, multidimensional datasets such as those from financial and supply chain markets. The CNN component excels at extracting critical spatial features from the data, such as patterns within the BDI and CCFI indices, which reflect the interconnectivity between financial and shipping sectors. At the same time, the LSTM network is designed to capture temporal dependencies, addressing the nonlinear, time-dependent fluctuations in market dynamics. The datasets include Chinese financial market data, featuring the BDI and CCFI indices, which represent the financial and supply chain sectors, respectively. The BDI, sourced from the Baltic Exchange—a prominent institution in the maritime industry—serves as a reliable benchmark for tracking the dynamics of the global dry bulk shipping market. Meanwhile, the CCFI, obtained from Clarkson Shipping, reflects container freight rate fluctuations in China's shipping industry. These indices are crucial for understanding the broader links between shipping and financial markets. Additionally, the financial dataset integrates real-time and historical data from major commodity trading platforms in China, including the China Financial Exchange and the Shanghai Stock Exchange. The dataset, spanning from 5 May 2015 to 30 November 2022, and comprising 25,974 observations, provides comprehensive insights into financial market conditions and supply chain performance. The training and test sets are divided in an 8:2 ratio. This extensive dataset serves as a robust foundation for training, testing, and evaluating the CNN-LSTM model, enabling more accurate forecasts by accounting for diverse market dynamics. For further details on the BDI and CCFI variables, please refer to Tables 1 and 2.

Table 1. Descriptive statistics of the BDI forecast data.

Variables	**Frequency**		**Abbreviation**		**Unit**
Baltic Dry Index	Day		BDI		Index
Rebar Futures	Day		RBFT		CNY/Ton
Copper Cathode Futures	Day		CUFT		CNY/Ton
Cotton Futures	Day		CFFT		CNY/Ton
Soybean No. 1 Futures	Day		YSAFT		CNY/Ton
Corn Futures	Day		YCFT		CNY/Ton
Thermal Coal Futures	Day		ZCFT		CNY/Ton
Coking coal Futures	Day		JMFT		CNY/Ton
Variables	**Count**	**Mean**	**Std.**	**Min.**	**Max.**
BDI	1788	1434.002	843.3825	295	5526
RBFT	1788	3585.982	932.0082	1630	6093
CUFT	1788	51,589.22	10,955.92	33,570	76,740
CFFT	1788	14,974.1	2612.233	9995	22,080
YSAFT	1788	4415.759	992.104	3139	6482
YCFT	1788	2087.368	454.4225	1392	3027
ZCFT	1788	617.1683	180.8696	282.2	1908.2
JMFT	1788	1395.018	593.8793	490	3781.5
BDI	1788	1434.002	843.3825	295	5526

The line graphs in Appendices A and B provide a visual representation of the trends for each indicator within the BDI and CCFI datasets from 5 May 2015 to 30 November 2022. These charts clearly illustrate the fluctuating patterns of each variable over recent years, serving as essential references for interpreting our model's results. By examining these line charts, we gain a nuanced understanding of trend patterns and periodicities for each indicator, which is crucial for interpreting the current and future trajectories of China's financial and maritime sectors. Additionally, these visualizations are instrumental in assessing the performance of our CNN-LSTM integrated model, offering valuable insights into the accuracy and robustness of the prediction outcomes. This understanding is vital for supporting sustainable development initiatives within China's financial and global maritime industries.

Table 2. Descriptive statistics of the CCFI forecast data.

Variables		Frequency	Abbreviation	Unit	
CHINA Container Freight Rate Index		Day	CCFI	Index	
Rebar Futures		Day	RBF	CNY/Ton	
Copper Cathode Futures		Day	CUF	CNY/Ton	
Gold Futures		Day	AGF	CNY/g	
Cotton Futures		Day	CFF	CNY/Ton	
Corn Futures		Day	YCF	CNY/Ton	
Thermal Coal Futures		Day	ZCF	CNY/Ton	
Coking Coal Futures		Day	JMF	CNY/Ton	
Variables	**Count**	**Mean**	**Std.**	**Min.**	**Max.**
CCFI	1096	1237.683	773.0506	743.71	3344.24
RBF	1096	3947.604	628.9994	2839	6093
CUF	1096	53,421.61	8689.881	36,630	76,740
AGF	1096	4335.984	752.9827	2928	6710
CFF	1096	15,100.18	2143.991	10,280	21,910
YCF	1096	2083.582	376.3864	1614	2890
ZCF	1096	645.4675	149.2798	481.2	1908.2
JMF	1096	1435.261	412.8718	943	3781.5

Correlation analysis, a foundational tool in machine learning, is essential for investigating relationships between variables and enhancing predictive model accuracy. A correlation heat map offers a visual overview of these relationships, with each cell's value indicating the strength of association between variables—higher values reflect stronger connections, while lower values suggest weaker associations. By exploring correlations among feature values, we can evaluate the influence of individual features on model predictions. Typically, a Pearson correlation coefficient above 0.7 indicates a strong positive correlation. The correlation matrices for the features in our dataset are shown in Figure 1, with the left panel illustrating the correlations within the BDI dataset and the right panel displaying those within the CCFI dataset.

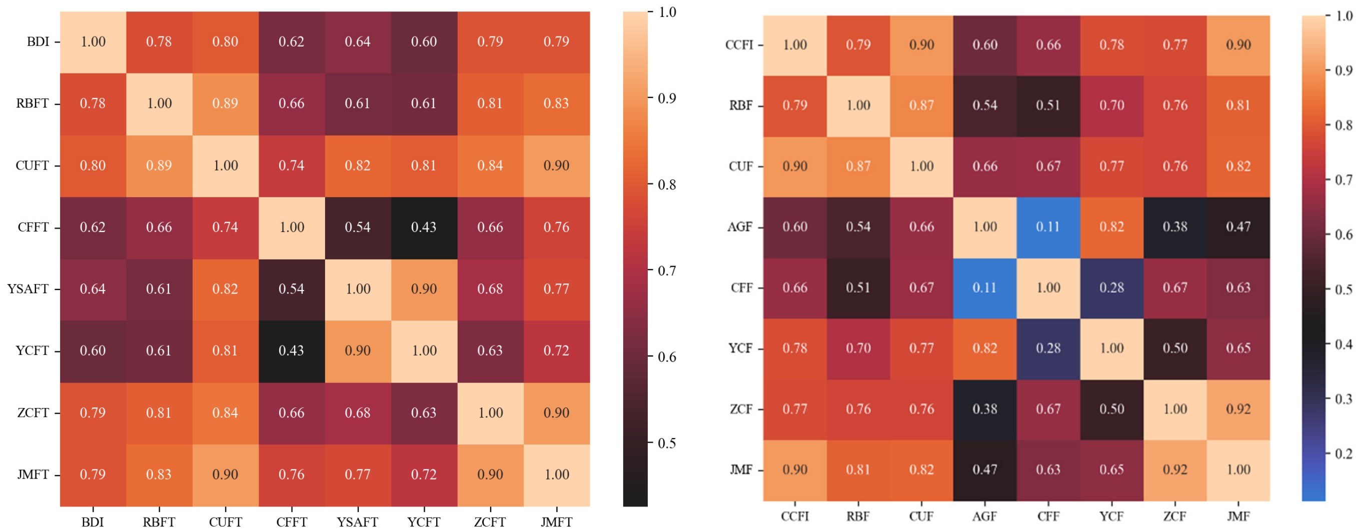

Figure 1. Heatmap illustrating the correlation matrix between the BDI and CCFI datasets. Note: the left panel shows the correlation heat map for the BDI dataset. The right panel shows the correlation heat map for the CCFI dataset.

3.2. Model

3.2.1. Convolutional Neural Networks (CNN)

The CNN, a powerful deep learning architecture, is highly effective at automatically extracting local features and identifying patterns in data through its convolutional layers. This capability makes it particularly suitable for processing sequence data with spatial structures [51]. When applied to BDI and CCFI forecasting, CNNs analyze time-series data, such as historical prices and trading volumes, to capture time-dependent and cyclical patterns. By uncovering these trends, CNNs enhance the accuracy of forecasts, supporting market participants in making more informed decisions about future market movements. The typical CNN architecture consists of key components such as convolutional layers, excitation layers, pooling layers, and fully connected layers, as depicted in Figure 2.

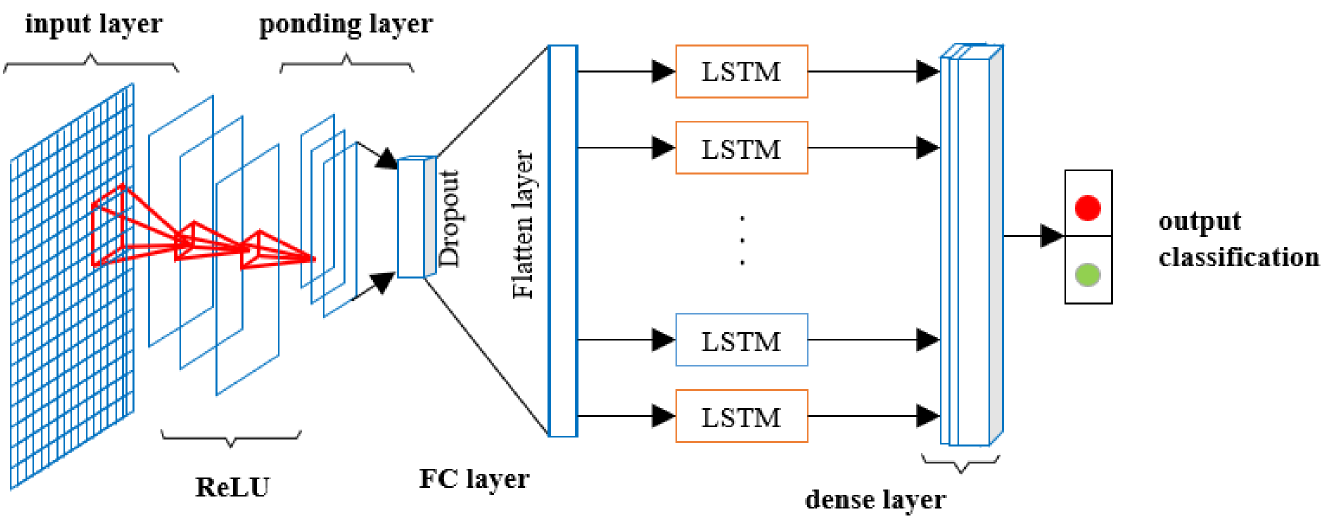

Figure 2. Convolutional neural network structure diagram.

Convolutional Layer

Feature extraction is achieved by using a convolution kernel to perform a convolution operation, which is characterized by local correlation and window sliding computation, and the output of the convolution operation is the feature matrix, which is shown in Equation (1) as follows.

$$y_{i\cdot j} = f\left(\sum_{m--\frac{k}{2}}^{\frac{k}{2}} \sum_{w=\frac{k}{2}}^{\frac{k}{2}} w_{m.n} x_{i+m\cdot j+\infty} + w_b\right) \quad (1)$$

In this context, x represents the input data; y is the convolutional output, indicating the data features; w is the convolutional kernel (also known as a filter, which is typically square in shape); k denotes the size of the convolutional kernel; i and j indicate the position of the output; m and n represent the position of the convolutional kernel; w_b is the bias term of w; and f stands for the activation function. The convolution operation perceives local features, and as the depth of the network increases, the perception becomes more global and abstract. The weight-parameter-sharing mechanism in the convolution operation, where the window slides, significantly reduces the number of parameters in the CNN compared to fully connected networks.

Incentive Layer

Following the convolutional layer, an activation function introduces nonlinearity to the neural network, ensuring the function is continuously differentiable. Commonly used activation functions include the Sigmoid function, the function, and the ReLU function, as shown in Figure 3. The activation function acts as a bridge between the output of the previous layer and the input of the next layer, with its derivative representing the gradient impact of the activation function. Through a comparison of function graphs, it can be noted that the gradients of sigmoid and tanh tend to wave zero as they approach the saturation region, whereas ReLU has a gradient of zero in the negative half-plane. The sigmoid and tanh functions are slower due to the inclusion of power operations. The ReLU function is computationally fast and converges quickly, making it the preferred activation function in convolutional neural networks due to its rapid iteration speed. Tanh can also be used as an alternative candidate activation function. The incentive layer and convolutional layers are combined into a single convolutional layer in the actual algorithm.

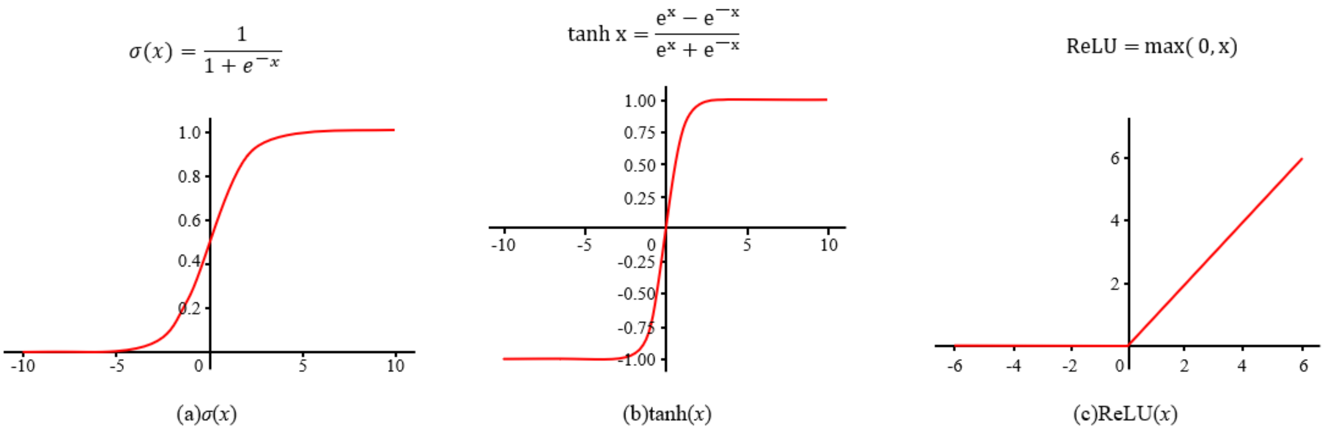

Figure 3. Sigmoid, tanh, and ReLU functions.

Pooling Layer

The pooling layer is positioned between consecutive convolutional layers and is used to compress data, reduce the number of parameters, and mitigate overfitting. It lowers the dimensionality of features while preserving the most important ones. The methods used in pooling layers include max-pooling, average-pooling, stochastic pooling, and global average pooling. Max-pooling is typically used to retain variability in features, selecting the maximum value from a matrix of height and width to represent the matrix region. The formula for Max-pooling is shown in Equation (2):

$$\text{maxpooling}[i,j] = \max(x[i \times \text{stride}_h + h, j \times \text{stride}_w + w]) \quad (2)$$

where maxpooling denotes the result of the pooling operation; $\boldsymbol{x}$ represents the input matrix; stride e_h and stride e_w denote the step sizes in the vertical and horizontal directions, respectively; and h and w represent the size of the pooling window.

Full Connectivity Layer

Typically, in the tail of a neural network, before the final output, the two-dimensional feature maps from the convolutional outputs are converted into one-dimensional vectors. Global average pooling (GAP) can also be used instead of, or added before, fully connected layers, as GAP can significantly reduce the number of weight parameters in the fully connected layer while preserving the features.

3.2.2. Long Short-Term Memory Network (LSTM)

LSTM is a specialized variant of the RNN that operates its storage unit by means of input gates, forgetting gates, and output gates. The output gate determines the amount of information that the LSTM unit will pass on to the subsequent time step, taking into account the current inputs and the hidden state from the previous time step, while the forgetting gate determines whether to retain or discard information based on the contents of the storage unit. The input gate is responsible for updating the state of the storage unit. The architecture of the LSTM is depicted in Figure 4 [52]. The LSTM's unique storage mechanism allows it to effectively capture long-term trends and cyclical variations within time-series data. This capability is particularly valuable for forecasting indices like the BDI and CCFI, as it involves the analysis of long-term price fluctuations, seasonal influences, and global economic factors. By doing so, the LSTM enhances the accuracy of forecasts and provides deeper insights into future market trends.

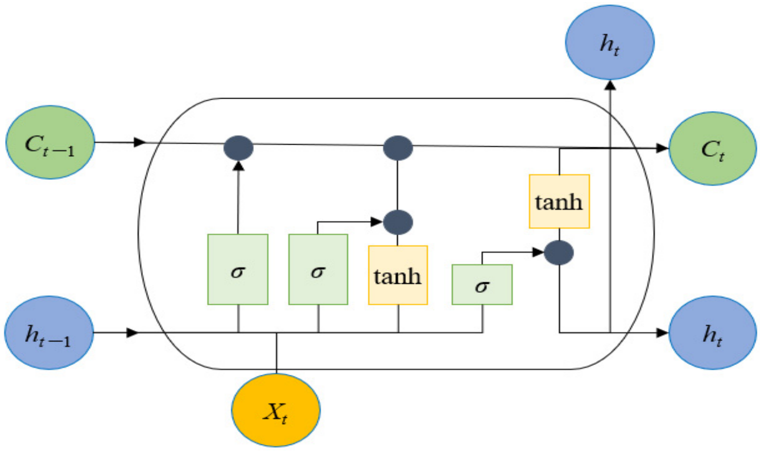

Figure 4. Long short-term memory network structure diagram.

The computation process for the forget gate, input gate, and output gate is as follows:

$$\begin{cases} f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \\ i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \end{cases}$$

In the equation: f_t, i_t, and o_t represent the computation results of the forget gate, input gate, and output gate, respectively; σ denotes the sigmoid function; W and b are the relevant weights and biases; h_{t-1} is the hidden state from the previous time step; and x_t is the sequence input at the current time step.

The computation process for the candidate state, updated state, and hidden layer output is as follows:

$$\begin{cases} \widetilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \\ c_t = f_t \cdot c_{t-1} + i_t \cdot \widetilde{c}_t \\ h_t = o_t \cdot \tanh(c_t) \end{cases}$$

In the equation, c_t and $\widetilde{c}_t$ represent the computation results of the candidate state and the updated state at the current time step, respectively; h_t denotes the output of the hidden layer at that moment; and tanh refers to the hyperbolic tangent function.

3.2.3. CNN-LSTM Model

As depicted in Figure 5, the CNN-LSTM model adeptly addresses the complex, multi-dimensional nature of BDI and CCFI data through its innovative architecture. The CNN component carefully extracts local features, effectively reducing data dimensionality while retaining essential temporal details. This refined data stream is then seamlessly transferred to the LSTM network, which efficiently captures long-term dependencies in the BDI and CCFI time series, leveraging its advanced time-series-processing capabilities. This combination significantly enhances prediction accuracy and deepens the model's understanding of intricate relationships within the datasets.

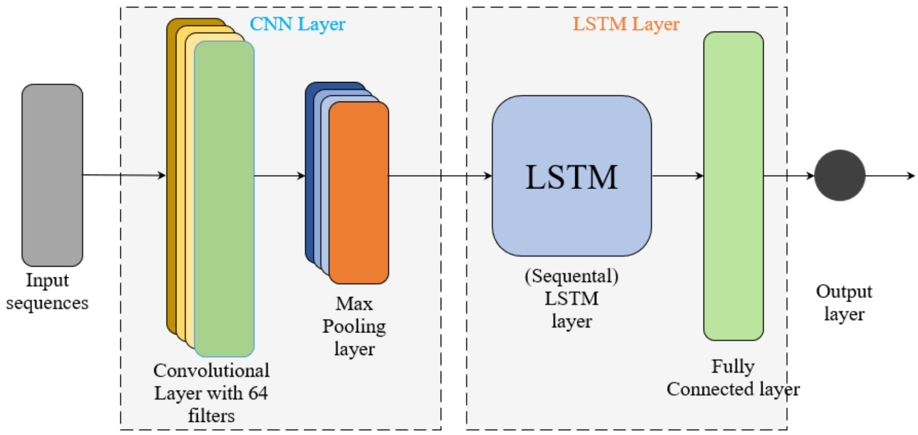

Figure 5. CNN-LSTM model.

By aligning the model architecture with the unique characteristics of maritime data—such as seasonal fluctuations in shipping demand and geopolitical influences on freight rates—the CNN-LSTM model interprets these domain-specific trends more effectively. This tailored approach not only boosts predictive performance but also strengthens its applicability in real-world scenarios, providing a robust foundation for optimized operations and risk mitigation in China's financial and maritime sectors. Additionally, the model supports sustainable development strategies by enhancing efficiency and forecasting accuracy, thereby contributing to the resilience and growth of the industry. Detailed parameter settings for the CNN-LSTM model for BDI prediction are provided in Table 3, and Table 4 outlines the parameters for CCFI prediction. For further parameter specifications, please refer to Appendix B.

Table 3. Parameters of the final CNN-LSTM model for BDI forecasting.

Layer (Type)	Output Shape	Param#
Input_1 (Input Layer)	[(None, 3, 8)]	0
conv1d (Conv1D)	(None, 3, 16)	400
conv1d_1 (Conv1D)	(None, 3, 32)	1568
lstm (LSTM)	(None, 3, 64)	24,832
flatten (Flatten)	(None, 192)	0
dense (Dense)	(None, 128)	24,704
dense_1 (Dense)	(None, 64)	8256
dense_2 (Dense)	(None, 1)	65
Total params: 59,825 Trainable params: 59,825 Non-trainable params: 0		

Table 4. Parameters of the final CNN-LSTM model for CCFI forecasting.

Layer (Type)	Output Shape	Param#
Input_5 (Input Layer)	[(None, 3, 8)]	0
conv1d_8 (Conv1D)	(None, 3, 16)	400
conv1d_9 (Conv1D)	(None, 3, 32)	1568
lstm _4(LSTM)	(None, 3, 64)	24,832
flatten_4 (Flatten)	(None, 192)	0
dense_12(Dense)	(None, 128)	24,704
dense_13 (Dense)	(None, 64)	8256
dense_14 (Dense)	(None, 1)	65
Total params: 59,825 Trainable params: 59,825 Non-trainable params: 0		

4. Results

4.1. Data Analysis Process

In this study, we evaluated three distinct models—CNN, LSTM, and CNN-LSTM—focusing on their predictive capabilities for the BDI and CCFI indices within Chinese financial data. Additionally, we compared the predictive performance of advanced models, such as BILSTM, with traditional models, including multiple linear regression (MLR), ridge regression (RIDGE), and Bayesian regression (BAYESIAN), to further validate the accuracy and applicability of our approach. To enhance the clarity of our findings, we incorporated a series of graphical illustrations.

Our preliminary analysis focused on the loss trajectories for each model as they predicted both the BDI and CCFI indices (refer to Figures 6 and 7). These trajectories serve as critical benchmarks for evaluating model performance across three key scenarios: underfitting, proper fitting, and overfitting. Underfitting occurs when the validation loss exceeds the training loss. In contrast, overfitting is indicated by a significant gap between the validation and training loss or by an upward trend in the validation loss. A proper fit is achieved when the training and validation loss curves converge. The vertical axis of the graphs represents the training and validation losses, while the horizontal axis denotes the number of iterations. The orange line illustrates the testing loss, and the blue line represents the training loss. These visualizations provide a clear comparison of model performance, allowing us to better understand the strengths and weaknesses of each approach in predicting the BDI and CCFI indices.

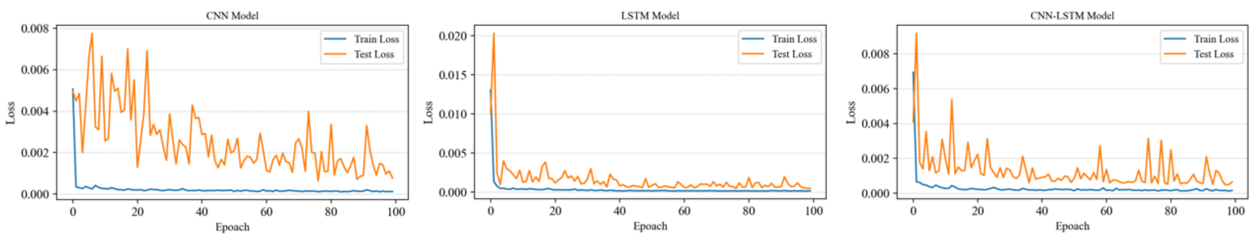

Figure 6. BDI loss function curves.

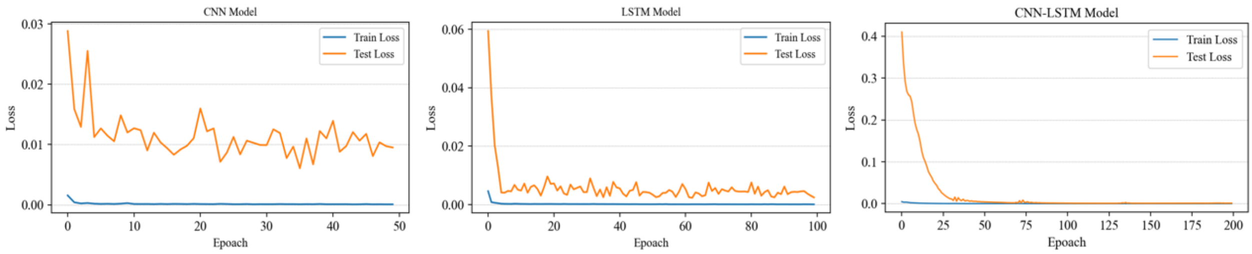

Figure 7. CCFI loss function curves.

As illustrated in Figures 6 and 7, our initial analysis examines the loss curves of the CNN, LSTM, and CNN-LSTM models during their predictions of the BDI and CCFI indices. These curves are essential for assessing model performance in three key scenarios: underfitting, optimal fitting, and overfitting. Underfitting is indicated when the validation loss exceeds the training loss, while overfitting is suggested by a significant discrepancy between the two losses or by an upward trend in the validation loss. The vertical axis of the graphs represents the training and validation loss metrics, while the horizontal axis charts the sequence of iterations during the training phase. The orange curve depicts the test loss, while the blue curve shows the training loss. This visual representation enables a concise evaluation of each model's learning efficiency and its ability to generalize to new, unseen data.

The training and test sets are split in an 8:2 ratio. As training progresses, the loss curves for both the training and validation sets gradually converge, indicating continuous improvement in model performance with each iteration. Among the three models, the CNN-LSTM demonstrates the most significant improvement, exhibiting the fastest and most stable convergence of the loss curves. This suggests that the CNN-LSTM model effectively learns from the training data and consistently produces robust, accurate predictions for both the BDI and CCFI indices. Its ability to maintain a low loss rate over a large number of iterations highlights its superior performance compared to the other models.

The CNN-LSTM architecture excels at capturing complex patterns and dependencies within the BDI and CCFI data, resulting in more reliable and precise predictions. This enhanced model performance across all scenarios underscores the strength of the CNN-LSTM model in predicting the BDI and CCFI indices, making it a valuable tool for real-world applications where accurate and consistent forecasts are essential for informed decision-making and strategic planning. Furthermore, the model's predictions closely align with the actual values in both datasets, reinforcing its robustness and reliability.

To further evaluate the performance of the CNN, LSTM, and CNN-LSTM models, we conducted a comparative analysis. Figure 8 presents the prediction outcomes for the BDI training set, prediction set, and actual values, while Figure 9 displays the corresponding results for the CCFI. These graphical representations will be used to succinctly summarize the overall performance comparison between the CNN, LSTM, and CNN-LSTM models.

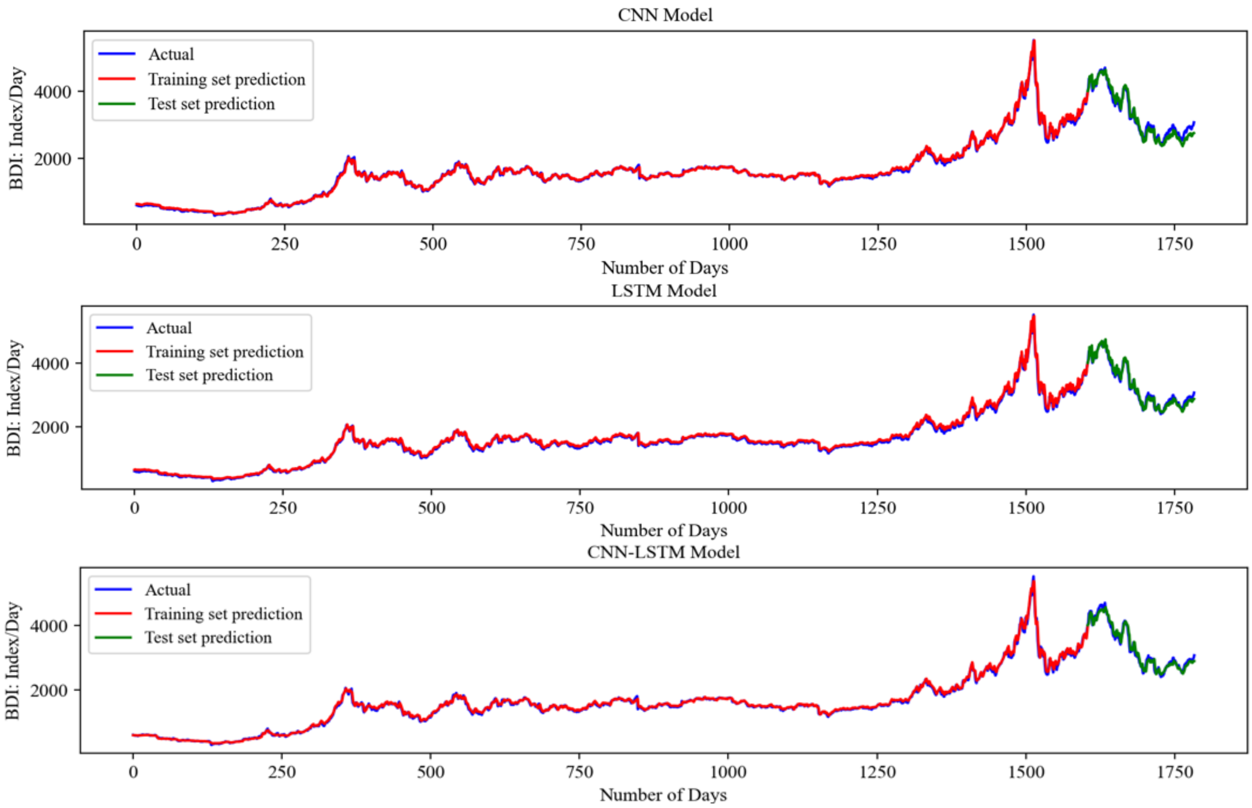

Figure 8. Comparative analysis of BDI data—raw, training, and testing phases.

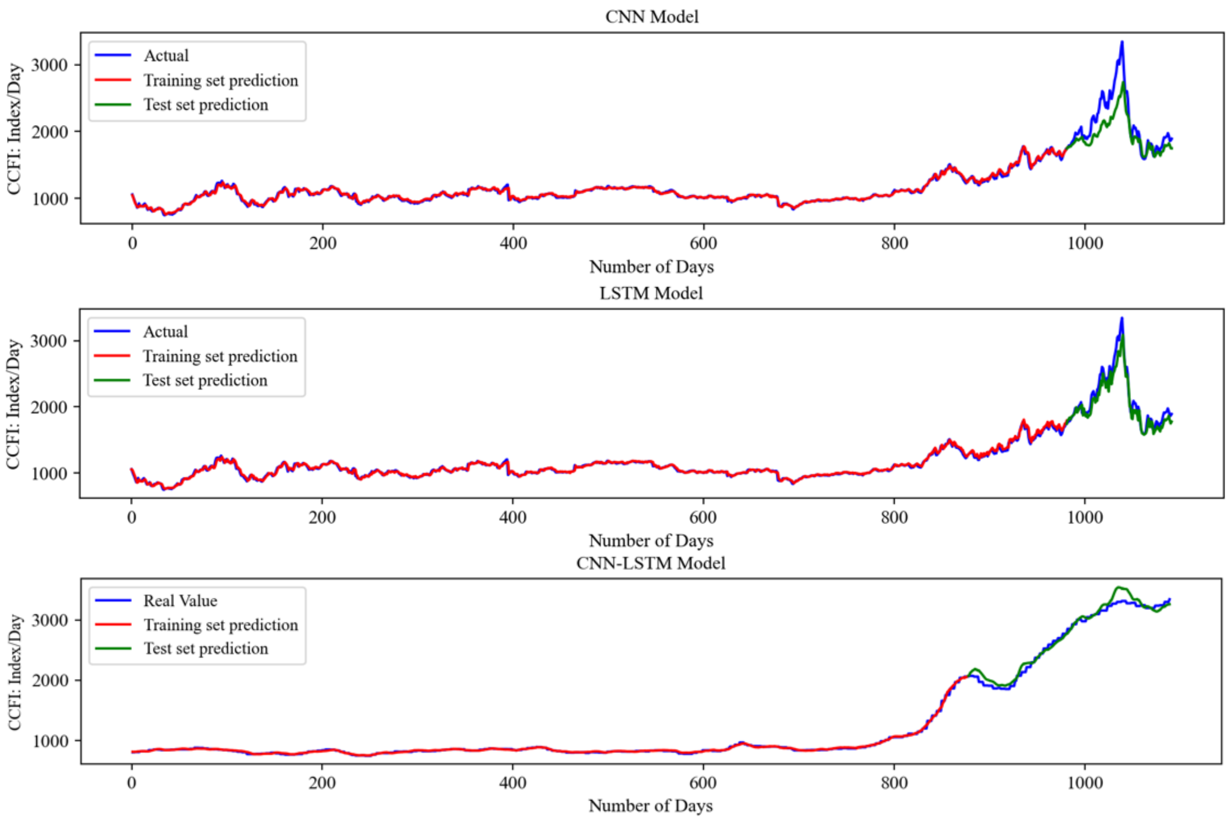

Figure 9. Comparative analysis of CCFI data—raw, training, and testing phases.

Figures 8 and 9 vividly illustrate the contrast between the raw data and the training and testing phases, clearly highlighting the advantages of the CNN-LSTM model. Across all six charts, the CNN-LSTM model consistently demonstrates superior performance, showcasing its exceptional ability to learn efficiently from the training dataset and generalize effectively to new data during the testing phase.

These charts provide a clear visualization of the training process, where the CNN-LSTM model exhibits the fastest convergence and the lowest loss rate. This rapid learning trajectory underscores the model's efficiency and adaptability. During the testing phase, the CNN-LSTM model continues to maintain a low loss rate, further emphasizing its robustness and its capacity to handle unseen data. This characteristic is crucial for any predictive model, as it ensures that the model's predictions are reliable and not overfitted to the training data. The model's strength is further reinforced by the close alignment of its predicted values with the actual data, confirming its accuracy in forecasting both the BDI and CCFI. This level of consistency is critical in the finance and shipping industries, where accurate BDI and CCFI predictions significantly influence sustainability and operational efficiency.

In conclusion, the CNN-LSTM model's consistent and stable performance on this dataset gives it a clear advantage in predicting the BDI and CCFI. Its robustness and precision make it a powerful tool in promoting sustainability within China's finance and shipping sectors. By providing reliable BDI and CCFI predictions, the CNN-LSTM model enables stakeholders to make informed decisions, optimize operations, and manage resources more effectively, thereby contributing to the overall sustainability of investments and related activities.

4.2. Model Assessment

In the context of performance assessment, the mean squared error (MSE) and the coefficient of determination (R^2) are employed as the primary evaluation metrics. The following are the mathematical expressions that represent these metrics:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_l)^2$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_l)^2}{\sum_{i=1}^{n} (\overline{y}_l - \hat{y}_l)^2}$$

Notes: The true value is denoted by y_i, the predicted value by $\hat{y}_l$, and the average value by $\bar{y}_l$.

Following 100 simulation iterations, the average R^2 scores for the three models were computed across both the training and test datasets. The comparative analysis presented in Tables 5 and 6 reveals that the CNN-LSTM integrated model demonstrates a marked superiority, boasting an R^2 value of 97.2% in both datasets. This intriguing and consistent outcome not only underscores the excellence of the CNN-LSTM model but also circumvents any debate regarding its superiority.

Table 5. BDI performance comparison by model.

Model	Train Set R^2	Test Set R^2	MSE	MAE
CNN	0.995	0.955	21,194.248	121.837
LSTM	0.993	0.963	12,379.631	88.841
CNN-LSTM	0.996	0.972	12,964.542	90.820
BILSTM	0.9863	0.9236	7,138,818.0237	2561.6285
MLR	0.7072	0.6626	210,697.2112	342.7191
RIDGE	0.7144	0.6360	251,171.1382	376.1386
BAYESIAN	0.7131	0.6223	211,194.2808	352.8514

Table 6. CCFI performance comparison by model.

Model	Train Set R^2	Test Set R^2	MSE	MAE
CNN	0.985	0.620	64,309.626	189.730
LSTM	0.982	0.908	15,617.316	96.046
CNN-LSTM	0.996	0.972	22,075.948	115.674
BILSTM	0.9971	0.8498	6,796,609.4641	2580.2486
MLR	0.9425	0.9087	45,191.4128	166.1732
RIDGE	0.9375	0.9340	39,718.1754	154.7130
BAYESIAN	0.9407	0.9151	39,349.5431	153.7079

5. Conclusions

The BDI and CCFI are critical indicators for the shipping industry, international trade, and the global economy. Developing accurate forecasting models for these indices is essential for effective investment and production planning, as well as for strategic decisions in e-commerce and supply chain management [24]. This study aimed to enhance the accuracy and sustainability of BDI and CCFI forecasts by introducing advanced forecasting models that can be applied to finance and shipping operations, including freight rate predictions. By enabling more precise forecasts, these models improve decision-making processes and optimize resource allocation, reduce unnecessary fuel consumption, and minimize environmental impacts. This aligns with global efforts to promote sustainable logistics practices, reduce emissions, and ensure the long-term viability of both financial and maritime industries.

Our research findings include the introduction of a novel deep learning integration strategy for predicting the BDI and CCFI. To improve the accuracy of these forecasts, we combined CNN and LSTM into a comprehensive suite of integrated deep learning models. We evaluated these models using a dataset of 25,974 observations from 5 May 2015 to 30 November 2022. The results highlight the significant advantages of the objectively optimized CNN-LSTM integrated model. The architecture of this model was carefully determined based on the validation set's performance metrics, employing an objective, data-driven approach. The model effectively captured the complex nonlinear features of BDI and CCFI data. In navigating various challenges—such as random sample selection, variations in data frequency, and structural breaks—the model demonstrated exceptional adaptability, refining hyperparameters like memory length, input variables, and training set size.

The CNN component excels at extracting local features from the BDI and CCFI data, identifying hidden nonlinearities to enhance prediction accuracy. Meanwhile, the LSTM component captures long-term temporal correlations, further improving the precision of forecasts. When benchmarked against standalone models, the CNN-LSTM integrated model outperformed both the individual CNN and LSTM models in predicting the BDI and CCFI, achieving an impressive R^2 value of 97.2%. This high R^2 value indicates that the model provides an exceptional and stable fit, accurately capturing the fluctuations in the BDI and CCFI.

In conclusion, the proposed CNN-LSTM ensemble model offers substantial advantages for BDI and CCFI prediction, particularly in ensuring the sustainable growth of the shipping and finance industries. By delivering reliable forecasts, this model empowers industry stakeholders to make more informed investment and production decisions, thereby contributing to enhanced operational efficiency and sustainability.

5.1. Theoretical Contributions

This research makes a substantial and multifaceted contribution to the field of machine learning, particularly at the intersection of sustainable finance and maritime transportation. One of the key breakthroughs is the integration of CNN and LSTM models into a cohesive deep learning framework. The findings conclusively demonstrate that the CNN-LSTM ensemble model outperforms individual machine learning models, significantly improving the accuracy of BDI and CCFI predictions. Additionally, the research provides novel insights into the intricate interplay between the BDI and CCFI and the myriad complicating factors affecting these indices. This aligns with and reinforces the work of [15], further validating the robustness of their findings.

Secondly, this study delves into the interdisciplinary relationships between China's financial and maritime markets, presenting a new analytical framework for understanding the dynamics of these interconnections. Although financial scholars have shown considerable interest in predicting the BDI and CCFI, there has been a relative scarcity of research exploring the link between these indices and the Chinese markets. Given China's vast demand for maritime transport and its rapidly expanding global freight sector, the influence of China's financial industry on the dynamics of the BDI and CCFI is becoming increasingly evident. In the context of economic globalization, it is crucial to thoroughly assess the role and impact of China's financial market in BDI and CCFI forecasting. This study examines the effectiveness of China's financial market in predicting freight rates, providing valuable insights for stakeholders. By accurately forecasting BDI and CCFI trends, investors can better identify opportunities and make more informed and strategic decisions. For participants in both the financial and maritime markets, this understanding enhances risk management and capital allocation, fostering sustainability in their operations.

The findings also support the hypothesis by [23], which posits a close connection between maritime transport and China's financial market. By expanding interdisciplinary research between the financial and maritime sectors, this study uncovers the complex interplay between China's financial market and the maritime industry. Ultimately, this research contributes to the sustainability of both finance and maritime transport by equipping stakeholders with tools and insights to navigate complex markets and make decisions that align with long-term environmental, social, and economic goals.

5.2. Managerial Implications

This research ingeniously leverages the predictive power of financial markets to forecast price trends in the freight sector, enhancing the economic efficiency of both financial and maritime markets. It begins by exploring the significant potential of deep learning methodologies in the domains of finance and maritime transportation, equipping stakeholders with innovative tools to predict fluctuations in financial and freight rates. This pioneering approach empowers trading managers to implement robust, competitive investment strategies. By providing real-time forecasting of the BDI and CCFI, companies can strategically adjust their trading plans, optimize resource allocation, and reduce operational costs. For investors, this timely intelligence facilitates proactive adjustments to investment strategies, allowing them to seize market opportunities more sustainably by promoting resource efficiency and reducing environmental impact through better decision-making.

Additionally, this study addresses the inherent volatility of financial and maritime markets, offering insights into market risk prediction. It helps companies and investors identify potential risks and develop effective mitigation strategies. For example, shipping companies can use BDI and CCFI forecasts to make informed decisions about trade, inventory, and procurement, reducing the effects of market volatility and contributing to more environmentally sustainable operations by minimizing fuel consumption and excessive resource use. Investors, in turn, can refine their portfolios in alignment with predicted trends in the BDI and CCFI, thereby fostering more sustainable risk diversification.

Moreover, this study provides valuable insights for governments and industry associations, offering a crucial reference point for understanding financial and maritime freight market conditions. By keeping abreast of BDI and CCFI forecast outcomes, these entities can develop policies that support the sustainable growth of the industry and promote green initiatives within both the financial and maritime sectors. Ultimately, this research strengthens the overall competitiveness of the financial and maritime industries, contributing to their stability, resilience, and sustainable development, while also supporting the global supply chains essential to economic prosperity.

5.3. Limitations and Future Research

While our research provides valuable insights, it is not without limitations. First, the CNN-LSTM integrated model was trained on a specific dataset with fixed parameters, which may limit its predictive accuracy due to the constraints of the data. Additionally, hyperparameters play a crucial role in model performance, and further investigation into automated methods for optimizing hyperparameter selection based on performance metrics is needed. Second, our study only incorporates a limited number of machine learning models. This may overlook the potential benefits of integrating additional high-performance models. Future research should compare our model with other nonlinear models to identify the most effective combinations. Lastly, we recommend expanding the dataset for future iterations to improve model accuracy. Market disruptions since 2020, such as the COVID-19 pandemic and the Suez Canal blockage, have highlighted the need to account for external uncertainties in BDI and CCFI predictions. Including such crisis-related variables as inputs and broadening the scope of market influences will enable more precise and resilient forecasting models. By addressing these areas, we aim to contribute to more robust, adaptable, and sustainable forecasting methods for financial and maritime markets.

Author Contributions: Conceptualization, Z.H. and X.Z.; methodology, Z.H.; software, Z.H.; validation, Z.H., X.Z. and Z.S.; formal analysis, Z.H.; investigation, Z.H.; resources, Z.H.; data curation, Z.H.; writing—original draft preparation, Z.H.; writing—review and editing, Z.H. and X.Z.; visualization, Z.H.; supervision, Z.S.; project administration, Z.S.; funding acquisition, Z.H. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data supporting the findings of this study will be made available upon request. Please contact the corresponding author at suzhenqing@kyonggi.ac.kr for access.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

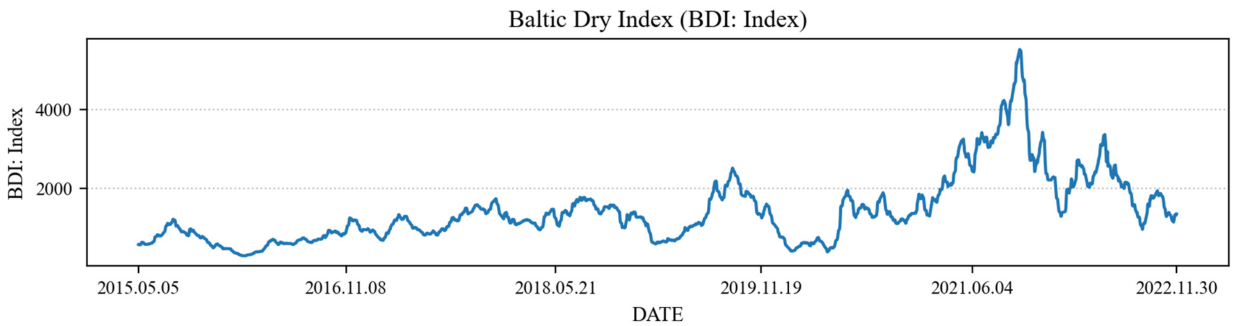

Figure A1. *Cont.*

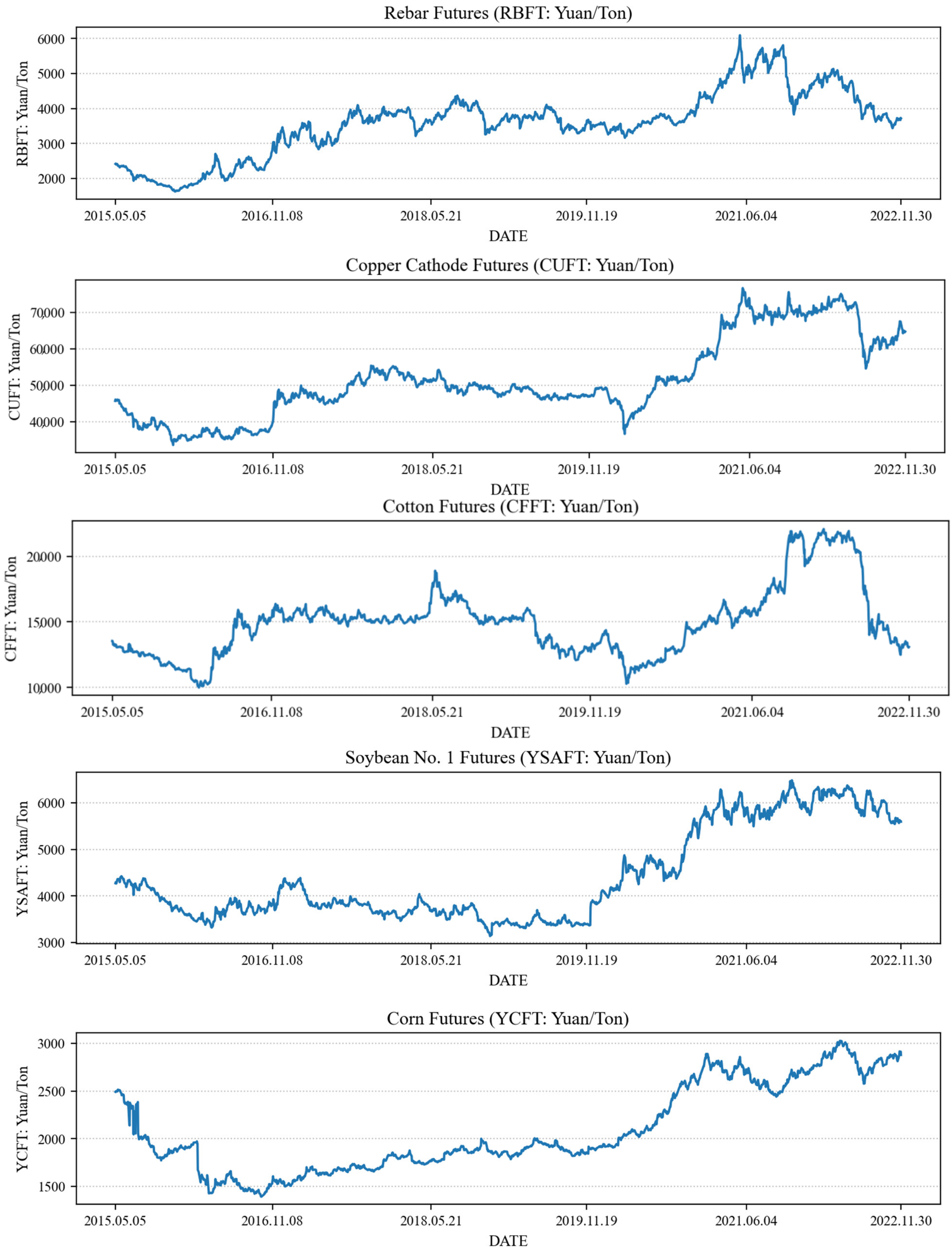

Figure A1. *Cont.*

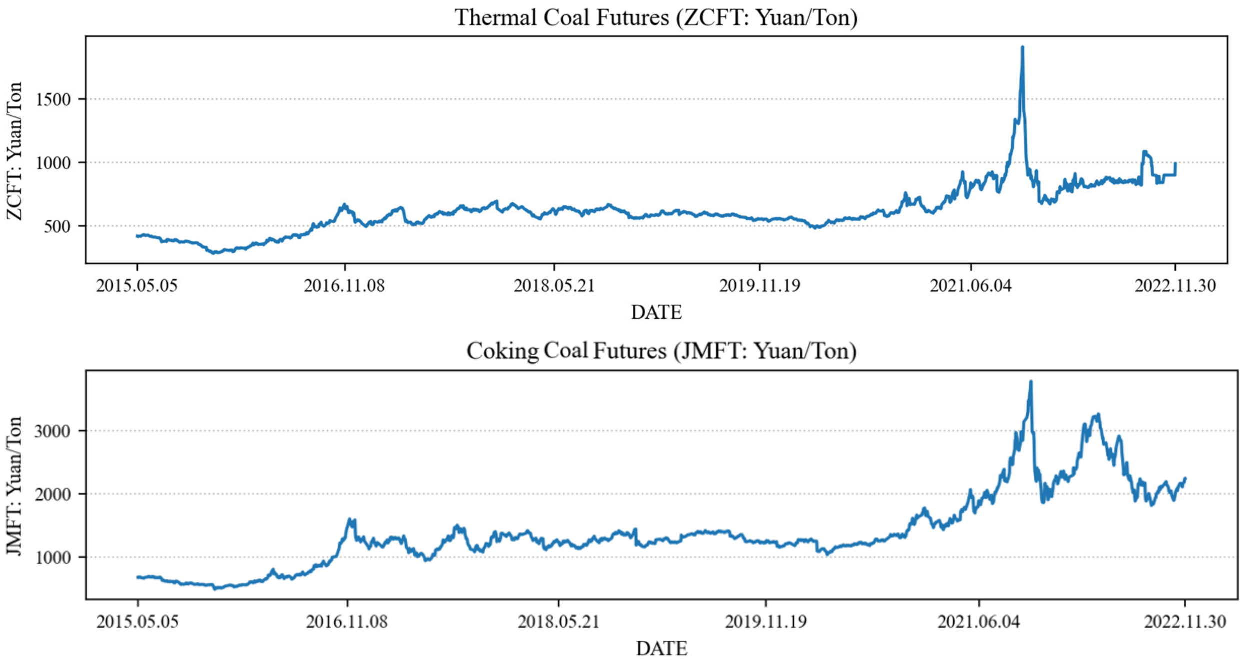

Figure A1. Line graph of BDI raw data.

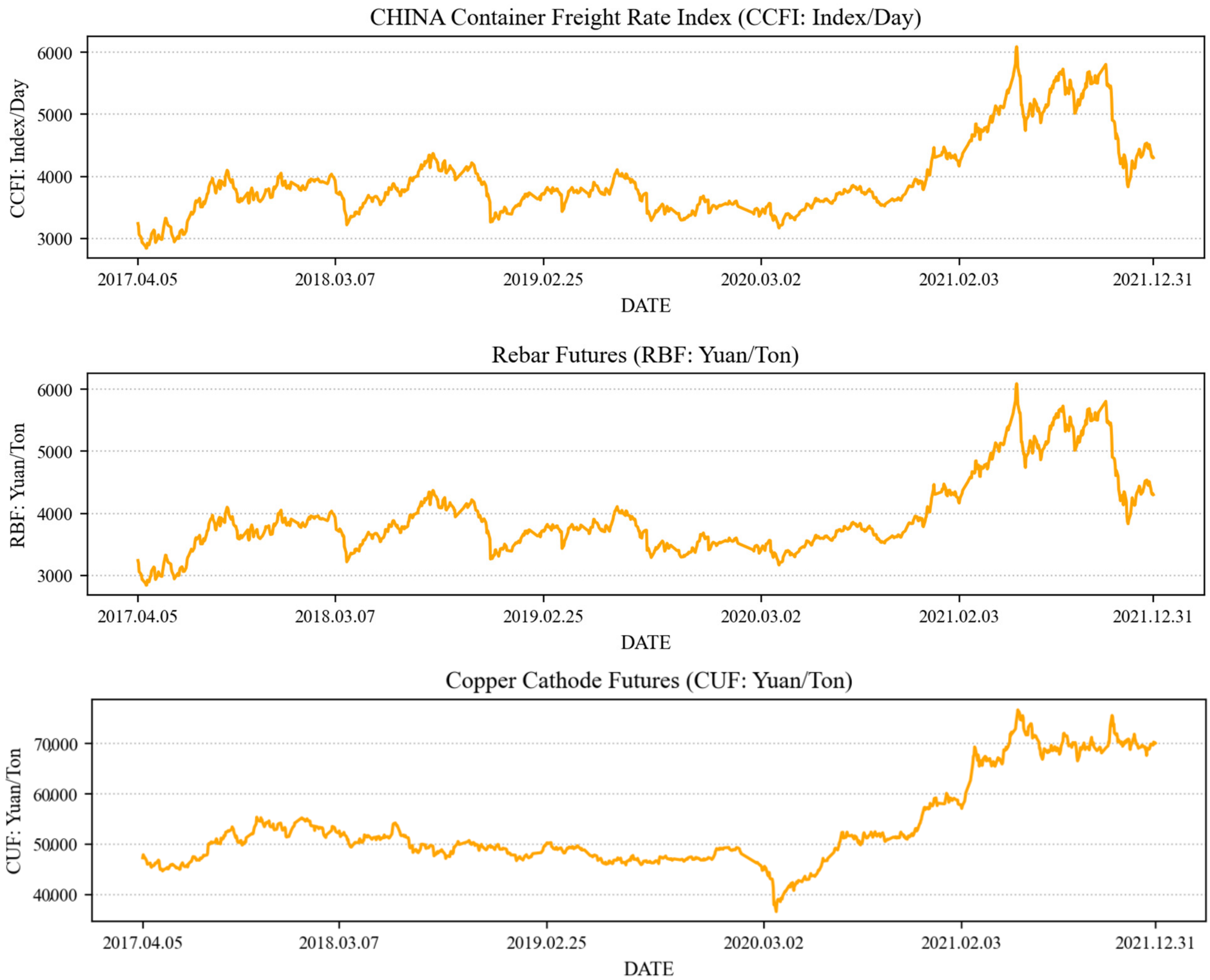

Figure A2. *Cont.*

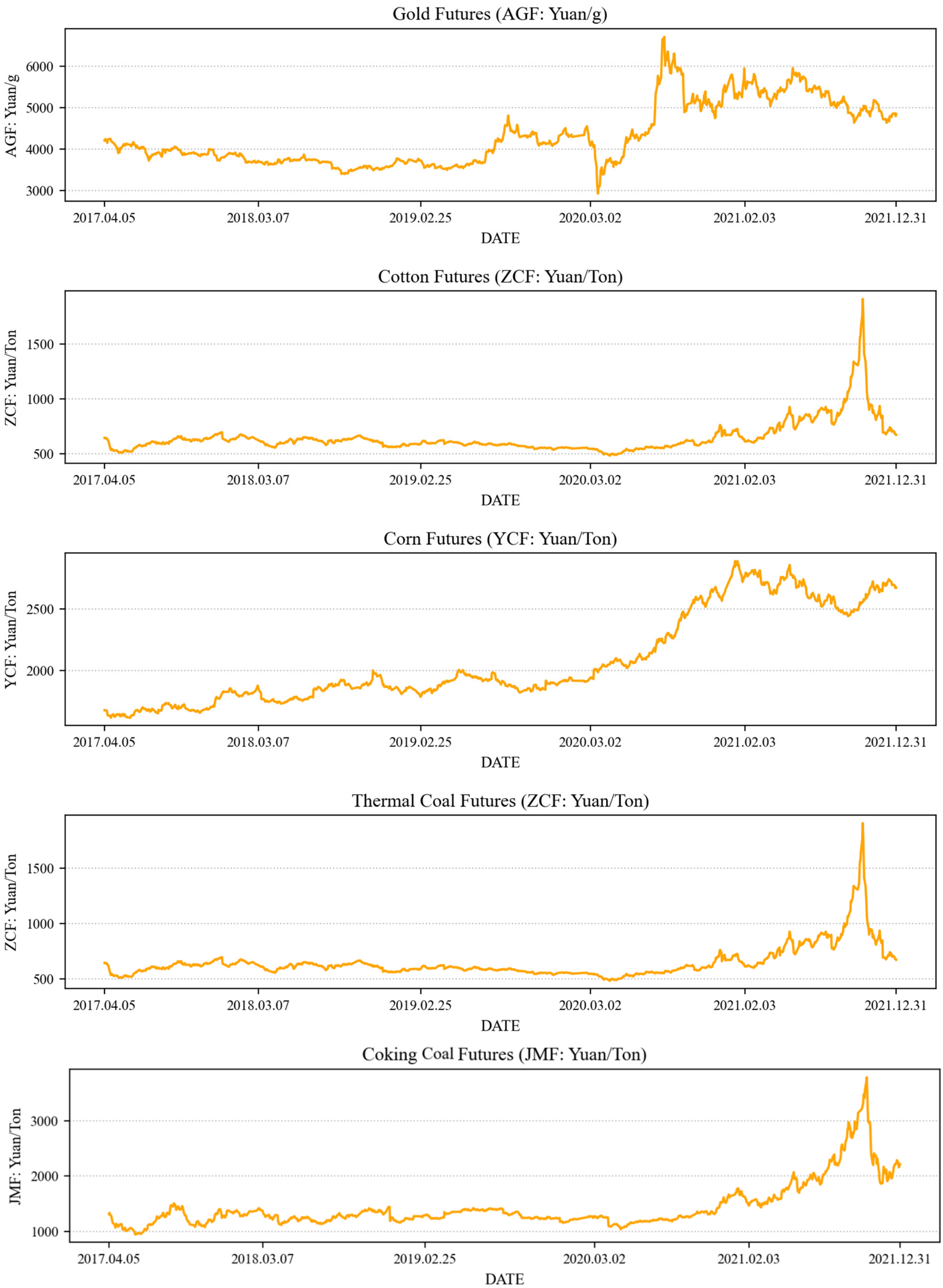

Figure A2. Line graph of CCFI raw data.

Appendix B

Table A1. BDI parameter setting table.

Hyperparameter	CNN	LSTM	CNN-LSTM
Hidden layer	2	2	2
Neurons	32	32	32
Optimizer	Adam	Adam	Adam
Batch size	16	16	16
Window size	7	7	7
Learning rate	0.001	0.001	0.001
Loss function	MSE	MSE	MSE
Filters	2		2
Kernel size	Relu		Relu
Activation	1		1

Table A2. CCFI parameter setting table.

Hyperparameter	CNN	LSTM	CNN-LSTM
Hidden layer	2	2	2
Neurons	32	32	32
Optimizer	Adam	Adam	Adam
Batch size	16	16	16
Window size	7	7	7
Learning rate	0.001	0.001	0.001
Loss function	MSE	MSE	MSE
Filters	2		2
Kernel size	Relu		Relu
Activation	1		1

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